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A REVIEW ON SPATIAL DOMAIN IMAGE SUPER-RESOLUTION AND VARIOUS CHALLENGE ISSUES

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ABSTRACT

Evaluating the previous work is an important part of developing super-resolution methods for better image reconstruction to improve perceptual quality with low computational complexity. image reconstruction has been very attractive research topic over last two decades as image super-resolution has a demanding applications in many of the real world applications such as, from satellite and aerial imaging to medical image processing, to facial image analysis, text image analysis, signature and number plate reading and biometric recognition. The aim of this paper is to review some spatial domain image super-resolution techniques as well as different challenge issues. This study is useful for accomplishing two goals (1) Reconstructing images without losing perceptual quality, (2) Designing new algorithms, the main objective.

KEYWORDS: Super-Resolution, Interpolation, Maximum A Posterior (MAP), Markov Random Field (MRF), Hallucination

I. INTRODUCTION

Image resolution describes the detail contained in an image. Super-resolution is the problem of generating a high resolution image from one or more low resolution images. When several low-resolution images are utilized to enhance the resolution, it is multi-image super-resolution. Multi-image SR basically works on the principle of combining nonredundant information contained in multiple LR frames to generate HR image. Whereas when HR image is obtained using single LR image, it is referred to as single image SR which can also be used to increase image size. In single image interpolation since, there is no additional information provided, the quality of this approach is very much limited due to ill posed nature of the problem as the lost frequency components cannot be recovered. However multiple-resolution observations are available for reconstruction making the problem better constrained in a manner that nonredundant information contained in these LR images by aligning them in a subpixel accuracy.

Many techniques have been proposed over last two decades representing approaches from frequency domain to spatial domain and from signal processing perspective to machine learning perspective. Many researchers worked on theory by exploring shift and aliasing properties of Fourier transformation. However, these observations are very restricted in the image observation model they can handle. Also, the real problems are much more crucial, researchers nowadays

most commonly address the problem mainly in spatial domain, so that it can be flexible to model all kinds of image degradation.

Although several articles have surveyed the different classical SR algorithms to extract HR images corrupted by the limitations of optical imaging system (Parulski et al,1992) such as finite aperture size, which causes optical blur modelled by point spread function, finite aperture time which results in motion blur, finite sensor size which results in sensor blur, the intension of this article is to pinpoint the various difficulties inherent to the SR problem as well as to enhance the image from LR frame which is degraded by downsampling and compression scenario. However images are degraded in order to reduce storage space and transmission bandwidth. Although this survey does not covers all the spatial domain SR analysis in detail, but provides comprehensive review of most of the SR works for each of the basic methods and, evolving path of the basic method have been discussed by providing the modification that have been applied to the basics by different researchers. The best thing about this paper is, this review is not only beneficial for the beginners in the field to understand the available methods, but also useful for the experts in the field to find out current status of their desired methods.

II. SPATIAL DOMAIN SR TECHNIQUES

In this section, we explore three specific SR scenarios. Many different researchers have optimized each specific SR scenario to better penalize trade off between preserving high frequency details and its computational complexity. Each of which technique addresses a particular aspect of the general SR challenge. It is our hope that this work provides the foundation for future work addressing more complete SR problem.

1. INTERPOLATION-RESTORATION

Basically, there are two criterions to evaluate the performance of an image interpolator: perceptual quality and computational complexity. Conventional nearest neighbour, bilinear and bicubic operators are simple with fast implementation, but they often introduce annoying “jaggy” artifacts around the edges because local directional features in images are not taken into consideration. Many algorithms [1]–[12] have been proposed to improve the subjective quality of the interpolated images by imposing more accurate models. Filtered back projection methods [1] were among the first methods developed for spatial based SR. Adaptive interpolation techniques [2]–[4] spatially adapt the interpolation coefficients to better match the local structures around the edges. Iterative methods such as PDE-based schemes [5], [6] and projection onto convex sets (POCS) schemes [7], [8], constrain the edge continuity and find the appropriate solution through iterations. Edge-directed interpolation techniques [9], [10] employ a source model that emphasizes the visual integrity of the detected edges and modify the interpolation to fit the source model. Other approaches [11], [12] borrow the techniques from vector quantization (VQ) and morphological filtering to facilitate the induction of high-resolution images. Among all the interpolation reconstruction, adaptive directional interpolation algorithm [13] is more competitive efficient compared with other methods, and it can be easily extended to any integer magnification ratios. Construction of Adaptive Directional Interpolator is threefold. First, gradients from LR image are diffused to the desired HR to determine the edge orientations at missing pixels in the magnified image. Second, linear interpolation with position fixed supports (i.e. involved known pixels) and gradient adaptive weights. Third, the continuities between original and interpolated pixels are enforced by difference projection, which simply reuses directional interpolator.

However, this approach does not include any additional information for compensating the high-frequency content of the HR images to be constructed, which has been lost in the low-resolution (LR) images. A number of super-resolution algorithms have employed regularization terms to solve the ill-posed image up-sampling problem. These algorithms usually incorporate smoothness priors as a constraint in reconstructing the HR images. However, using smoothness priors that are defined artificially has been found to lead to overly smoothed results. Moreover, the interpolation based approaches need special treatment of limited observations in order to reduce aliasing without HR image prior as proper regularization.

2. STATISTICAL IMAGE RESTORATION

There are some statistical approaches [14]-[30] in which SR reconstruction is related stochastically towards optical reconstruction. The HR image and motions among LR inputs can be both regarded as stochastic variables. These methods for enhancing image sequences using motion information needs motion to be estimated by various motion estimation methods. After motion computation, assuming prior distribution of degradation matrix, this knowledge is integrated into a Bayesian SR framework or uses the degradation bounds to determine convex sets which constrain the SR problem. SR reconstruction can be cast into full Bayesian framework

$$\mathbf{X} = \arg\max_X \int_{v,h} \frac{\Pr(\underline{Y}|X, M(v,h)) \Pr(X, M(v,h))}{\Pr(\underline{Y})} dv \tag{1}$$

Here, M(v,h) is the degradation matrix defined by motion vector v and blurring kernel h, $\Pr(\underline{Y}|X, M(v,h))$ is the data likelihood, Pr(X) is the prior term on the desired HR image and Pr(M(v,h)) is the prior term on the motion estimation. Assuming M to be known, the Bayesian formulation in Eqn. 1 is further simplified to form popular MAP for SR,

$$\mathbf{X} = \arg\max_X \Pr(\underline{Y}|X, M) \Pr(X)$$

$$= \arg\min_X \{||\underline{Y} - MX||^2 + \lambda A(X)\} \tag{2}$$

Where λ absorbs the variance of noise. If uniform prior over X is assumed Eqn. 2 is reduced to simplest maximum likelihood estimator. The ML estimator relies on the observations only, seeking the most likely solutions for the observations to take place by maximising P($\underline{Y}|X$).

Statistical image reconstruction methods has shown potential to improve image resolution as compared to conventional filtered back projection method. According to the MAP estimation, the SIR methods can be typically formulated by an objective function consisting of two terms: (1) Data fidelity (or equivalently, data- fitting or data mismatch term) modelling the statistics of projection measurements, and (2) Regularisation term reflecting prior knowledge or, expectations on the characteristics of the image to be reconstructed.

2.1 Maximum a Posterior (Map) Estimation

Mathematically, reconstruction of low resolution images degraded by down sampling and compression is an ill-posed problem due to the presence of quantization noise and other inconsistencies in the projection data. Therefore, the image estimation that directly optimizes the (ML) maximum likelihood criterion can be very unstable and noisy. This problem is reformulated by researchers with the MAP estimation by posing a prior term to penalize or regularize the solution. The prior term enables us to incorporate available information or expected properties of the image to be reconstructed. The MAP estimator mathematically can be written as:

$$\mu^* = \arg \max_{\mu} P(\mu \| N) \tag{3}$$

According to the Bayesian law:

$$P(\mu|N) = \frac{P(N|\mu)P(\mu)}{P(N)} \tag{4}$$

By taking the logarithm and omitting the irrelevant term, the MAP estimator can be simplified to:

$$\mu^* = \arg \max_{\mu} [\ln P(\mu|N)] = \arg \max_{\mu} [(\mu|N)] = \arg \max_{\mu} [L(\mu|N) + \ln P(\mu)] \tag{5}$$

It can be simplified as:

$$\mu^* = \arg \max_{\mu} [L(N|\mu) - R(\mu)] = \arg \max_{\mu} [L(N\|\mu) - \beta U(\mu)] \tag{6}$$

where U (μ) denotes a penalty, and $\beta > 0$ is a scalar control parameter which allows one to tune the MAP (or penalized ML) estimation for a specific noise-resolution tradeoff. When β goes to zero, the reconstructed image from the MAP estimation approaches the ML estimation.

The MAP estimation from the Tikhonov regularization point of view, can be considered as an objective function consisting of two terms: a data-fidelity term (e.g, the log-likelihood) modeling the statistics of projection measurements, and a regularization term (e.g, the log-prior) incorporating prior knowledge or expected properties of the image to be reconstructed. The resulting objective functions in Eqn. (6) would be concave if and only if U (μ) is a convex function of μ. Hardie *et al.* [24] proposed a joint MAP framework for simultaneous estimation of the high resolution image and motion parameters with Gaussian MRF prior for the HR image. Bishop *et. al* [25] proposed a simple Gaussian process prior where the covariance matrix Q is constructed by spatial correlations of the image pixels. The Gaussian process priors due to its good analytical property allows a Bayesian treatment of the SR reconstruction problem, where the unknown high resolution image is integrated out for robust estimation of the observation model parameters (unknown PSFs and registration parameters). Although the GMRF prior has many analytical advantages, a common criticism for it associated with super-resolution reconstruction is that the results tend to be overly smooth, penalizing sharp edges that we desire to recover. Again to encourage piecewise smoothness and to well preserve edges, image gradients are modelled with a distribution with heavier tails than Gaussian, leading to the popular Huber MRF where the potentials are determined by Huber function,

$$\rho(a) = \begin{cases} a^2 & |a| \le \alpha \\ 2\alpha|a| - a^2, & otherwise \end{cases} \tag{7}$$

Here, a is the first derivative of the image. Schultz and Stevenson [14] applied this Huber MRF to single image expansion problem, and later to the SR reconstruction problem in [22]. Many later works on SR employed the Huber MRF as the regularization prior, such as [17]-[23]. Total variation norm (TV) has a gradient penalty function is also very popular in image denoising and deblurring literature[26,27,28]. Total amount of change in the image as measured by the ℓ_1 norm of the magnitude is efficiently regularized. Magnitude gradient is given by

$$F(X) = \| \nabla X \|_1 \tag{8}$$

Mainly, statistical image reconstruction techniques are adopted for clinical use to compute X ray CT and also in Emission tomography modalities. Statistical techniques have several attractive features [29]–[30]. The data noise is statistically modelled by offering the potential for better bias-variance performance. Statistical methods also easily incorporate the system geometry, detector response, object constraints and any prior knowledge. They can also model such phenomena as scatter and energy dependence leading to more accurate and noise-free reconstruction. Mostly they are suited for arbitrary geometries and situations with truncated data. Their main drawback is longer computation times. For clinical CT images with typical sizes of 512 $\times$512 pixels or larger, conventional statistical methods require prohibitively long computation times which hinder their use.

3. LEARNING BASED RESTORATION

Different from previous approaches, learning based methods rely on super-resolving LR image using single LR image. Unlike previous methods where priors are in parametric form regularizing on the whole image, the example based methods develop the prior by sampling from other images similar to [31],[32] in a local way. One family of this class approaches [33] to exploit neighbourhood relationships in SR algorithm by Markov network to probabilistically model the relationships between high- and low-resolution patches, and between neighbouring high resolution patches. It uses an iterative algorithm, which usually converges quickly. Such approaches usually work by maintaining two sets of training patches, $\{x_i\}_{i=1}^{n}$ sampled from the high resolution images, and $\{y_i\}_{i=1}^{n}$ sampled from the low resolution images correspondingly. Each patch pair (x_i, y_i) is connected by the observation model $y_i = DHx_i+V$. This high- and low-resolution co-occurrence model is then applied to the target image for predicting HR image in a patch based fashion.

3.1 Markov Model

Spatial relationships between patches is modelled using a Markov network, which has many well-known uses in image processing. In Figure 1, the circles represent network nodes, and the lines indicate statistical dependencies between nodes. We let the low-resolution image patches be observation nodes, y. We select the 16 or so closest examples to each input patch as the different states of the hidden nodes, x. that we seek to estimate. For this network, the probability of any given high-resolution patch choice for each node is proportional to the product of all sets of compatibility matrices relating the possible states of each pair of neighboring hidden nodes, and vectors relating each observation to the underlying hidden states:

$$p(x\,|y) = \frac{1}{Z}\Pi_{i,j}\,\Psi_{ij}\left(x_i, x_j\right)\Pi_i\,\phi_i\left(x_i, y_i\right) \tag{9}$$

Z is a normalization constant, and the first product is over all neighboring pairs, i and j. yi and xi are the observed low-resolution and estimated high-resolution patches at node i, respectively. To specify $\Psi_{ij}(x_i, y_i)$ function, the sum of squared differences of the patch candidate x_i and x_j , $dij(x_i, x_j)$ is measured in their overlap region *i* and *j*. Assuming σ as a noise parameter, compatibility matrix between nodes *i* and *j* is,

$$\Psi_{ij}(x_i, x_j) = \exp\left(\frac{d_{ij}(x_i, x_j)}{\sigma^2}\right) \tag{10}$$

With a Markov random field(MRF) model as shown in Figure 1. The observation model parameters are assumed to be known as a prior, also tight coupling of target image with training sets is needed. Optimum patch size should be selected. If patch size is too small, the co-occurrence prior becomes too weak to make meaningful prediction. While if patch size is very large, a huge training set is needed to find proximity patches for current observation.

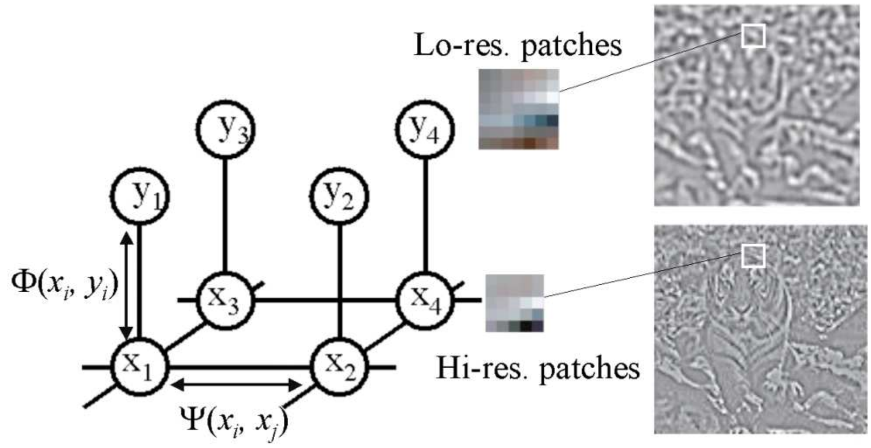


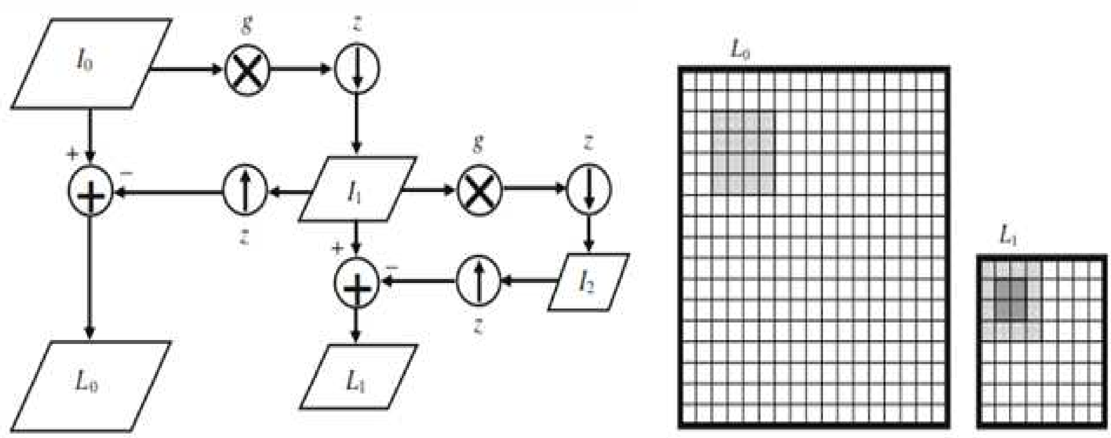
Figure 1: Markov Network Model for the SR Problem. The LR Patches at Each Node Y_i are the Observed Input. The HR Patch at Each Node X_i is the Quantity We Want to Estimate

Baker and Kanade [34, 35], have demonstrated that reconstruction constraint used in many regularization based methods provides less useful information as the zooming factor increases. They proposed a "Hallucination Algorithm" to break the limit of reconstruction constraint. To estimate the high frequency components for the HR image, a multiscale feature vector from a training set, which is composed of both LR details and its corresponding HR details, is searched as the best match, based on the LR patches from a LR image and the LR pixel values of the feature vector. Most example based SR algorithms [36]-[40] also involve a training set, which is usually composed of a large number of HR patches and their corresponding LR patches. The input LR image is segmented so as to create patches which could be either overlapping or no-overlapping. Then, for each LR patch from the test image, either one best-matched patch or a set of the best-matched LR patches is selected from the training set. The corresponding HR patches are used to reconstruct the output HR image. Freeman et al. [36, 37] embedded two matching conditions into a Markov network. One is that the LR patch from the training set should be similar to the input observed patch, while the other condition is that the contents of the corresponding HR patch should be consistent with its neighbours. Wang et al. [38] extended the Markov network to handle the estimation of PSF parameters. Stephenson and Chen [39] presented a method in which the symmetry of a cropped human face is considered in the Markov network. Qiu [40] proposed an alternative method, based on vector quantization, to organize example patches. A survey of example-based super-resolution methods is available in [41].

However, most of these existing algorithms involve only a kind of ‘‘searching and pasting” approach, and are therefore computationally intensive when searching for a LR–HR patch from a huge training set. Furthermore, best-matched but incorrect patches will seriously degrade the reconstruction results. To deal with these problems, usually the algorithms simply adopt the average of a set of the ‘‘best-matched” patches; the averaged high-frequency component is then pasted into the magnified image. For example, Qiu [40] employed the ‘‘classifying and averaging” scheme. However, the averaging will result in over-smoothing in the output HR image. Li [41] employed class-specific predictors so as to have efficient learning from separate class-specific database. The prior term learned discussed above imposes the local constraints of the super-resolved image, while for imposing global constraints, some SR algorithms have used projection

based methods for learning the a priori term of the employed MAP algorithm, a Kernel-PCA based prior that is a non-linear extension of the common PCA was embedded in a MAP method to take into account more complex correlations of human face images. In PCA based methods, usually the matrices representing each training image are first vectorized (by arranging, e.g, all the columns of each matrix in only one column) and then they are combined into a large matrix to obtain the covariance matrix of the training data for modeling the eigenspace. It is discussed in [42] that such vectorization of training images may not fully retain their spatial structure information. Instead, it is suggested to apply such a vectorization to the features extracted from training data and use them for SR.

3.1 How to Design and Generate Training Database?



(a) **(b)**

Figure 2: (a) Generation of the HR Difference Image L_0 and the LR Difference Image L_1 for the Construction of HR-LR Patches, and (b) A 4*4 HR Block in L_0 and its Corresponding LR Block in L_1

The training set chosen for exercise is essential to the realization of the learning-based super-resolution methods. Each record in the training set is an example patch-pair, viz. a HR image block and the corresponding LR block. Similar to the method proposed by Qiu [40], a multi-resolution representation of an input image is formed using a three-level Laplacian pyramid. As shown in Figure 2 (a), let I_0 represent a HR example image, which is blurred and down-sampled to produce I_1 by a zooming factor z. similarly, I_2 is generated from I_1 using same zooming factor z. The up sampled images from I_1 and I_2 are generated using bilinear interpolation with a factor z, and are then subtracted from I_0 and I_1, respectively to compute difference images L_0 and L_1. The example patch pairs are then extracted from L_0 and L_1, which are then used to train up the predictors.

Figure 2(b) shows a HR difference image L_1. If z=2, each 4*4 HR block in L_0, e.g. the grey block has a corresponding 2*2 LR block in L_1.. viz. the black block. In order to maintain the continuity of a HR block with its neighbors, we extend the boundary of the corresponding LR block by 1 pixel to form a LR sampling block, i.e. the LR block in black and the neighboring pixels in grey in L_1, as shown in Figure 2(b) This HR block and the corresponding LR sampling block thus form a patch-pair. By considering all the possible HR blocks in L_1. and the corresponding

LR sampling blocks a training set in the patch pairs is generated. Example based algorithm works best when data's resolution or noise degradation match those of the images to which it is applied.

4. SR WITH COMBINED METHODS

In order to better solve SR problem, some researchers combined the above algorithms resulting in new groups of algorithms. Examples of such category can be found in: [47] and [48]: where ML and POCS are combined, which allows incorporating non-linear a priori knowledge into the process.

- [49] and [50]: MAP and POCS are combined and applied to compressed video.
- [51]: MAP and FBP are combined.
- [52] and [53]: where reconstruction based SR is followed by learning based SR.

III. CHALLENGE ISSUES

In this article, we presented only a few methods and insights for specific scenarios of Super-Resolution. Many questions still persist in developing a generic Super-Resolution algorithm capable of producing high-quality results on general image sequences. Furthermore, analysis of this sort could possibly provide understanding of the fundamental limits to the Super-Resolution imaging, thereby helping practitioners to find the correct balance between expensive optical imaging system and image reconstruction algorithms. Such analysis may also be phrased as general guidelines when developing practical super-Resolution systems.

In building a practical Super-Resolution system, many important challenges lay ahead. For instance, in many of the optimization routines used in this and other articles, the task of tuning the necessary parameters is often left up to the user. Parameters such as regularization weighting λ can play an important role in the performance of the Super-Resolution algorithms. Although the crossvalidation method can be used to determine the parameter values for the nonrobust Super-Resolution method (Nguyen et al, 2001a), a computationally efficient way of implementing such method for the robust Super-Resolution case has not yet been addressed. Although some work has addressed the joint task of motion estimation and Super-Resolution (Hardie et al, 1997; Schultz et al,1998; Tom and Katsaggelos, 2001), the problems related to this still remain largely open. Another open challenge is that of blind super-Resolution wherein the unknown parameters of the imaging system's PSF must be estimated from the measured data. Many single-frame blind deconvolution algorithms have been suggested in the last 30 years (Kondur and Hatzinakos, 1996), and recently (Nguyen et al, 2001a) incorporated a single parameter blur identification algorithm in their Super-Resolution method, but there remains a need for more research to provide a Super-Resolution method along with a more general blur estimation algorithm from aliased images. Also, recently the challenge of simultaneous resolution enhancement in time as well as space has received growing attention (Robertson and Stevenson 2001; Shechtman et al, 2002).

Adding features such as robustness, memory and computation efficiency, color consideration, and automatic selection of parameters in super-Resolution methods will be the ultimate goal for the Super-Resolution researchers and practitioners in the future.

IV. CONCLUSIONS

This paper reviews most of the papers on Spatial domain Super-Resolution and also proposes broad anatomy for the same. Supplementary to giving details of most of the techniques, it notifies the pros and cons of the method when they have been available in the reviewed paper. Furthermore, it highlights the most common challenge issues encountered while

dealing with them.

This overview has come to its tail end, but one can still not answer to the very important question, what are the state-of-the-art Super-Resolution algorithms. Truly speaking, the answer is highly dependent on the application. The SR algorithm which is good for clinical imaging is not necessarily good for aerial images or facial image processing. In different algorithms, different algorithms are leading. That's why there still are many recent publications for almost all types of the surveyed algorithms. This is mainly due to the different constraints that are imposed on the problem in different applications. Therefore, it seems difficult to compare super-resolution algorithms for different applications against each other. Generating the touchstone database for learning examples seems quite challenging. Generally speaking, comparing frequency domain algorithms with spatial domain, former are very interesting from the theoretical point of view but faces many problems when applied to real world scenarios e.g, spatial domain methods have better evolved with proper modeling of the motion in real world applications. Frequency domain methods mostly lacks in this. That's why there still are many recent publications for almost all types of the surveyed algorithms. This is mainly due to the different constraints that are imposed on the problem in different applications. Therefore,it seems difficult to compare super-resolution algorithms for different applications against each other. Among these methods, the single-image based methods are more application-dependent while the multiple image based methods have been applied to more general applications. The multiple-image based methods are generally composed of two different steps: motion estimation, then fusion. These had and still have limited success because of their lack of robustness to motion error (not motion modeling). Most recently, implicit nonparametric methods have been developed that remove this sensitivity, and while they are slow and cannot produce huge improvement factors, they fail very gracefully and produce quite stable results at modest improvement factors.

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